How technology paradoxes and self-efficacy affect the resistance of facial recognition technology in online microfinance platforms: Evidence from China

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Abstract

This study aims to figure out the antecedents of users' resistance behavior toward facial recognition technology (FRT) in the microfinance platforms of China. We proposed a theoretical model by combining the technology paradox framework and self-efficacy theory. There were 418 valid questionnaires collected via an online survey. This study demonstrates, using structural equation modeling (SEM), that self-efficacy significantly affects technology paradoxes, anxiety, and resistance. Moreover, it suggests that the relationship between technology paradoxes and anxiety varies, and users are more concerned about the dissatisfiers of technology paradoxes (inefficiency and public). Besides, a positive correlation was found between anxiety and resistance. Finally, the results of the mediating effects test show that self-efficacy can not only directly affect resistance, but also indirectly influence it through efficiency, public, and anxiety. This study provides a deeper insight into users' resistance behaviors toward FRT and has significant implications for managers, technology designers, and future researchers.

Keywords: facial recognition technology (FRT), microfinance, technology paradoxes, self-efficacy, anxiety, resistance.

1. Introduction

During the past decade, artificial intelligence (AI) has revolutionized society with the advancement of a range of novel technologies, such as big data, machine learning, and deep learning. It utilizes computers to perform human-intelligence activities by acquiring knowledge, analyzing and studying the expression methods of knowledge (Da Xu et al., 2021; Zhang & Lu, 2021). In recent years, AI has emerged as a powerful and indispensable instrument for social development, especially with the spread of COVID-19 around the world.

As a critical element of AI technologies, facial recognition technology (FRT) has seen remarkable developments in the past few years. Currently, FRT plays an ever-increasing role, and new applications for FRT emerge in response to COVID-19. In China, for example, FRT was used to measure body temperature and track the activity history of infected patients during the epidemic (Ashta & Herrmann, 2021; Shamman et al., 2021). It is one of the pivotal biometric methods (e.g., voice, fingerprint, iris, face) and works by matching users' facial figures with existing images stored in the database. Compared with passwords or PINs, FRT is more accurate and secure since facial features cannot be stolen, forgotten, or guessed (Sukhija et al., 2016). Also, since there is no physical contact or interaction, it can be easier to use than other methods of identification and authentication (Elloumi et al., 2021). This is especially helpful in light of the current pandemic.

China has been at the global forefront of developing and applying FRT (Kostka et al., 2021). Compared with many other countries testing the technology itself instead of its application, China has established the FRT system and made it widely available for commercial use (Elloumi et al., 2021; Zhong et al., 2021). As early as 2017, China’s e-commerce giant Alibaba first deployed FRT to a KFC restaurant for payment. Currently, FRT has been widely used for security systems, access control, and video surveillance in various places (Coşkun et al., 2017), such as stores, hospitals, schools, airports, hotels, restaurants, government agencies, and even social networks (Heyer et al., 2018; Lai & Patrick Rau, 2021). According to a report by Gen Market Insights, China is expected to reach 44.59% of the global market share in 2023 and become the largest consumption area of FRT devices (Gravett, 2020).

FRT is also finding its way into the finance sector as a robust identification and authentication method. For example, banks have introduced it into the identification process in ATMs to improve security. Besides, with the rapid increase in mobile devices, mobile payment has become ubiquitous in China (Chen et al., 2019). Financial institutions have attempted to introduce FRT to support their mobile payment transactions to deliver more secure and convenient services. Indeed, face recognition payment (FRP) has been appreciated by users for its convenience.

The emergence and development of online microfinance platforms in China also provides opportunities for FRT usage. Generally, these platforms based on information and communication technology (ICT) tools (e.g., computers, the internet, websites, mobile devices) deliver financial services and provide both group and individual lending. (Moro-Visconti, 2021). They are gradually replacing traditional credit and are even inseparable from the daily consumption of the Chinese. For example, Ant Credit Pay, a microfinance service initiated by Alibaba, is widely used by Chinese consumers for early consumption and online shopping (Shi, 2020). Another example is Ali Finance, established in 2011 and provides loans to customers trading on the Alibaba and Taobao platforms (Ali, 2020; Tu et al., 2018). They have been updating their functions and applications, including incorporating FRT into the platforms (Liu, 2015; Zhong & Nieminen, 2015). For example, it uses FRT to extract and recognize the borrowers' facial features to assess their credibility and predict repayment performance (Chen & Xu, 2019). In fact, FRT has been used by most microfinance platforms in China to support their online transactions.

However, like many emerging technologies, FRT has turned out to be a controversial technology and is faced with challenges. Although security, accuracy, and convenience have been emphasized, there has been an increase in discussions about its disadvantages. Of particular concern are privacy issues (Brinckerhoff, 2018; Hirose, 2016; Mazura et al., 2012; NNG de Andrade et al., 2013; Wilkinson, 2020). As pointed out by Brinckerhoff (2018), FRT introduces privacy risks by collecting and storing customers' biometric data. In fact, the Chinese public hesitates to use FRT or even opposes it. According to a survey in 2019, 75% of over 6000 Chinese citizens preferred traditional recognition methods rather than FRT (Kostka et al., 2021). Similarly, the latest investigation in 2021 revealed that 87% of over 1500 respondents opposed FRP use. Nevertheless, some studies have suggested that Chinese users care more about convenience than privacy. For instance, Che et al. (2021) found that the rapid adoption of FRT in China is related to Chinese people's low level of concern for privacy protection through a comparative analysis. That means Chinese resistance to FRT may not only be attributed to their privacy concerns. Apart from further verifying whether privacy-related factors are relevant, it is necessary to take other factors into consideration, such as functional factors (like efficiency) and psychological factors (like self-efficacy).

Chae and Yeum (2010) highlighted that technology contains conflicts since it simultaneously has bright and dark sides. While customers can benefit from technologies, they may also have opposite experiences (Johnson et al., 2008). These paradoxical experiences then induce conflicts and negative feelings, such as anxiety and stress, which prevent customers from using technologies. In terms of FRT, individuals may perceive that it interferes with their daily lives instead of saving them time or increasing their security (Brown et al., 2021). Even if it is convenient and can help them save time, it can be time-consuming due to specific factors like lightning and camera characteristics. Another example is that users still take the risks of leaking personal information despite being protected by the platform's privacy policies. Even though customers often experience these conflicts when using FRT, researchers have often ignored its paradoxes.

To fill this gap, the current study employed the technology paradox framework (Jarvenpaa & Lang, 2005; Mick & Fournier, 1998) and expanded it by introducing self-efficacy theory. Thus, this research aims to appraise the degree to which technology paradoxes (efficiency/inefficiency and private/public) and self-efficacy influence users' anxiety and resistance toward FRT. The findings reported here contribute to the microfinance literature on ICT tools' usage. This study provides managers, technology designers, and future researchers with deeper insight into the users' resistance behavior toward FRT usage.

2. Literature review

2.1 Facial recognition technology and innovation resistance

2.1.1 Facial recognition technology

FRT is a technology that compares and identifies individual facial features (Kostka et al., 2021; Unar et al., 2014) and is widely used for identification and authentication in various industries (Ciftci et al., 2021; Leong et al., 2020b). As one of the most commonly used biometrics, it has been the subject of a lot of research and has been used in a wide range of fields, including healthcare (Jeon et al., 2019; Zuo et al., 2019), retail (Elloumi et al., 2021; Moriuchi, 2021), restaurants, hospitality and travel (Ciftci et al., 2021; Morosan, 2019, 2020; Xu et al., 2021), criminal identification (Purshouse & Campbell, 2019), as well as banking and finance (Normalini & Ramayah, 2013; Piotrowska et al., 2017).

In the banking and finance industry, Feng et al. (2017) pointed out that FRP, identification, and withdrawals are three primary applications of FRT. Being a robust authentication method, FRT is anticipated to promote the development of mobile finance (Caldwell, 2012). It provides customers with convenience and reduces costs to a large extent (Piotrowska et al., 2017; Zheng et al., 2019). Early studies have examined various variables that influence the customers' intentions to adopt FRT in the finance text. For example, Gatali et al. (2016) suggested that it was privacy concerns, education, and laws that restricted the Canadian banking industry from adopting biometrics, not technological issues. Agidi (2018) argued that security and efficiency are the keys to getting banks all over the world to use biometrics.

It is worth noting that abundant empirical research has been undertaken on FRP. These studies focused predominantly on exploring the factors influencing user experience and usage intention. Compared with traditional payment methods, FRP could trigger more privacy concerns as it can identify and monitor users without their permission (Erkin et al., 2009). Furthermore, users' acceptance of FRT has also been reported to be influenced by privacy-related variables, including perceived privacy risk, privacy concerns, and privacy control (Ioannou et al., 2020; Li et al., 2020; Liu et al., 2021). Although there are privacy risks in using FRP, users could also enjoy the convenience, security, and other benefits it brings (Prabhakar et al., 2003). Accordingly, some previous researchers focused on the performance of FRP systems and analyzed factors such as security, ease of use, and usefulness. For instance, Zhang and Kang (2019) discovered that security, safety, expected effort, and visibility were antecedents of behavioral intentions. Both Dong and Hai (2019) and Zhong et al. (2021) suggested that perceived usefulness and perceived ease of use were major drivers of usage intentions utilizing the technology acceptance model (TAM) proposed by Davis (1989). In addition, psychological factors such as self-efficacy have also been found to influence users' behavioral intentions toward FRP. For instance, Moriuchi (2021) discovered that self-efficacy had moderating effects on perceived risk, performance expectation, and usage intention by combining the unified theory of acceptance and use of technology (UTAUT) and the theory of mind (ToM). Therefore, it is necessary to integrate privacy-related factors, functional factors, and psychological factors to examine users' acceptance of FRT.

While there has been increasing awareness of the importance of exploring the customers' intention to use FRT in the finance industry, little attention has been given to FRT usage in the microfinance field. During the past decade, microfinance has received much limelight in academia, and considerable research effort has concentrated on topics like its impact, sustainability, efficiency, outreach, financial inclusion, and entrepreneurship (Field et al., 2013; Gutiérrez-Nieto & Serrano-Cinca, 2019; Hermes & Lensink, 2011; Mushtaq & Bruneau, 2019). In addition, the role of ICT in microfinance has also been examined by previous studies (Kauffman & Riggins, 2012; Riggins & Weber, 2016; Singh & Padhi, 2015). For instance, Kauffman and Riggins (2012) argued that ICT is a potential solution for microfinance to face the harsh environment and survive. According to Ashta and Herrmann (2021), credit scoring based on AI technologies helps microfinance institutions (MFIs) to understand their customers better and lower risks. However, few investigations into FRT applications can be found in these studies.

2.1.2 Innovation resistance

Innovation resistance is a negative response to changes brought about by innovation (Ram, 1987). As with acceptance and adoption, innovation resistance is an essential element of consumer behaviors (Seth et al., 2020). Understanding consumer resistance, according to academics and experts, is the key to ensuring that new technologies are accepted and utilised (Talwar et al., 2020).

Typically, most research on technical innovation focuses on “usage intention” or “continuance intention”. These studies biasedly assumed that people are eager to adopt and employ new technologies and products (Talke & Heidenreich, 2014). However, the negative outcomes that people are reluctant to change are often ignored. Therefore, for the controversial FRT technology, it is necessary to investigate the antecedents of users’ resistance to it.

Up to date, various consumer resistance models have been established to explore the major factors influencing users’ resistance to new technologies (Abbas et al., 2017; Hew et al., 2019; Kaur et al., 2020; Kleijnen et al., 2009; Leong et al., 2020a; Liu et al., 2021; Mani & Chouk, 2017; Matsuo et al., 2018; Tang & Chen, 2022). For instance, Kleijnen et al. (2009) proposed a consumer resistance model and attributed the resistance to conflicts and the degree of change needed. Mani and Chouk (2017) analyzed the factors that affected users’ resistance to smart products from the perspectives of products and consumers. Lee (2020) proposed that users’ resistance to home Internet of Things (IoT) services was assosiated with vulnerability factors and privacy concerns.

However, there are a handful of studies exploring the fundamental mechanism of resistance to FRT. Gao et al. (2021) found that customers were less likely to use FRP despite requiring less effort and time because of the social presence effect. Liu et al. (2021) found significant relationships between perceived effectiveness of privacy policy, privacy concerns, perceived privacy risk, and users’ resistance to FRP. Table 1 summarizes the literature exploring the usage intention of using FRP.

2.2 Technology paradoxes

Handy (1994) explained that a paradox is the simultaneous presence of opposing claims or assumptions. Consumers’ experiences with novel technologies are often paradoxical (Johnson et al., 2008), and FRT is no exception. That means, while technology is performing its functions, it also brings about opposite results or situations (Chae & Yeum, 2010). These contradictory qualities of technologies can provoke consumers’ conflicting perceptions (positive or negative attitudes) (Park & Zhang, 2021). By analyzing consumers’ experiences of using household technologies, Mick and Fournier (1998) proposed the technology paradox framework, including paradoxes as follows: control/chaos, freedom/enslavement, new/obsolete, competence/incompetence, efficiency/inefficiency, fulfills/creates needs, assimilation/isolation, and engaging/disengaging. According to this framework, technology paradoxes could provoke the sentiments of conflict, anxiety, and stress. Besides, in the context of mobile technologies, Jarvenpaa and Lang (2005) added two more paradoxes—planning/improvisation and public/private. Recent authors have further put forward the categorization of technology paradoxes. For example, Wilson-Nash and Tinson (2021) identified six paradoxes in the use of digital technology by the elderly, including an original paradox—attachment/non-attachment. They divided these paradoxes into functional, social, and psychological paradoxes.

Early studies have applied technology paradoxes to a variety of contexts. For example, both Johnson et al. (2008) and Bulmer et al. (2018) investigated the technology paradoxes experienced by those consumers of self-service technology. The former found paradoxes in this setting included freedom/enslavement, fulfills needs/creates needs, control/chaos, whereas the latter argued four paradoxes existed: efficiency/inefficiency, fulfills needs/creates needs, control/chaos, competence/incompetence. Based on a proposed research model, Chae and Yeum (2010) demonstrated that efficiency/inefficiency, new/obsolete, empowerment/ enslavement, and engaging/disengaging were significantly related to stress about mobile technologies. Moreover, Zhuang et al. (2013) empirically found that the paradoxes arising from the use of social networking sites involved assimilation/isolation and competence/incompetence. Lee and Rha (2016) proposed that the personalization-privacy paradox significantly affected internal conflict and the continued use intentions towad mobile commerce. Additionally, by integrating technology paradoxes and technology readiness, Park and Zhang (2021) demonstrated that customers ready to use unmanned convenience stores perceive the satisfiers of technology paradoxes more.

While considerable theoretical effort has been put into technology paradoxes, no studies on the paradoxes of FRT users are available, especially with empirical methods. As mentioned above, FRT users are also experiencing paradoxical perceptions because of the pros and cons of FRT. For example, as there is no need to enter a password, FRT can help users save time. However, the efficiency and accuracy of recognition are also affected by many factors, such as make-up, the color of skin, aging, occlusion, and plastic surgery (Anwarul & Dahiya, 2020; Lohr, 2018; Ueda & Koyama, 2010). Thus, users may not only perceive the efficiency of FRT but also perceive its inefficiency. Another central issue is privacy. Face recognition data has been required to be additionally protected by relevant laws to protect privacy (Wilkinson, 2020). While those technology companies with access to personal information have made their privacy policies, FRT users are still concerned about the misuse of personal information and privacy violations (Carpenter et al., 2018; Li et al., 2020; Morosan, 2019). Consequently, it is necessary to involve technology paradoxes to explore usage intention for FRT, especially focusing on two primary technology paradoxes—efficiency/inefficiency and private/public.

The COVID-19 pandemic spurs an increase in FRT use due to its safety, convenience, and ability to assist in maintaining physical distance. Insight into the antecedents influencing the behavior of FRT users and the role of their feelings is essential in the adoption and management of FRT. Although the ongoing crisis has increased the importance of FRT, the paradoxes that FRT users are experiencing have not been investigated. Therefore, the present study aims to empirically examine how technology paradoxes and self-efficacy influence the resistance of FRT in China's online microfinance platforms. By combing functional factors (efficiency/inefficiency), privacy-related factors, and psychological factors (self-efficacy), we proposed a theoretical model that reveals to managers, policymakers, and technology designers the underlying causes of users' resistance to FRT.

2.3 Self-efficacy

Self–efficacy is the principal concept of social cognitive theory, and it refers to one's judgment about one's capacity to undertake specific actions (Bandura et al., 1997). In terms of technology applications, self-efficacy refers to people's belief that they possess the necessary expertise and abilities to utilise technology (Holden & Rada, 2011). In this way, self-efficacy is one's judgment or estimation of his/her abilities rather than his/her actual abilities. Hence, this study defined self-efficacy as one's perception or judgment of his/her capability to use FRT. Researchers have introduced self-efficacy into the context of technology applications involving computers (Compeau & Higgins, 1995; Isman & Celikli, 2009; Kinzie et al., 1994), the internet (Lai, 2008; Torkzadeh & Van Dyke, 2001), mobile technologies (Abulibdeh & Hassan, 2011; Tilton & Hartnett, 2016; Yang, 2012), and robotics (Latikka et al., 2019; Turja et al., 2019).

Self-efficacy influences people's behavioral decisions and how much effort they put into those behaviors, which is crucial for technology acceptance and adoption (Barling & Beattie, 1983). Previous studies have shown that self-efficacy positively affects consumers' attitudes and behavioral intentions toward new technology (Jokisch et al., 2020; Kumar et al., 2020; Mitzner et al., 2019; Ratten, 2013). People with high self-efficacy, according to these research, generally have a positive attitude. They are more open to new technologies due to their confidence in their ability to learn and use them (Conrad & Munro, 2008). Even though Moriuchi (2021) has shown that self-efficacy moderates the effect of behaviorial intentions on self-efficacy, there is not much evidence that self-efficacy has a direct or indirect effect on

FRT usage intentions.

In addition, self-efficacy has also been proven to be related to perceived ease of use (Brown, 2002; Saadé & Kira, 2009), privacy concerns (Akhter, 2014; Dienlin & Metzger, 2016), and anxiety (Onyeizugbo, 2010; Powell, 2013). These relationships suggest that self-efficiency is also related to factors in the technology paradox framework, such as efficiency/inefficiency, private/public, as well as anxiety. For example, high self-efficiency can make people more confident in completing work and managing personal information efficiently. Furthermore, people with low self-efficacy may experience anxiety due to a lack of confidence in their ability to use technology, which makes them resistant to using new technologies. Accordingly, to examine the factors influencing technology acceptance, it is necessary to investigate the connections between self-efficacy and these factors (Ratten, 2013). To this end, we introduce self-efficacy to the technology paradox framework to assess how it interacts with other factors (efficiency/inefficiency, private/public, anxiety) and how it affects user resistance in direct or indirect ways.

3. Research model and hypotheses

Figure 1 provides our research framework with all variables—self-efficacy, technology paradoxes, anxiety, and resistance. Technology paradoxes here are comprised of efficiency, private, inefficiency, and public. The operational definitions of these constructs are shown in Table 2.

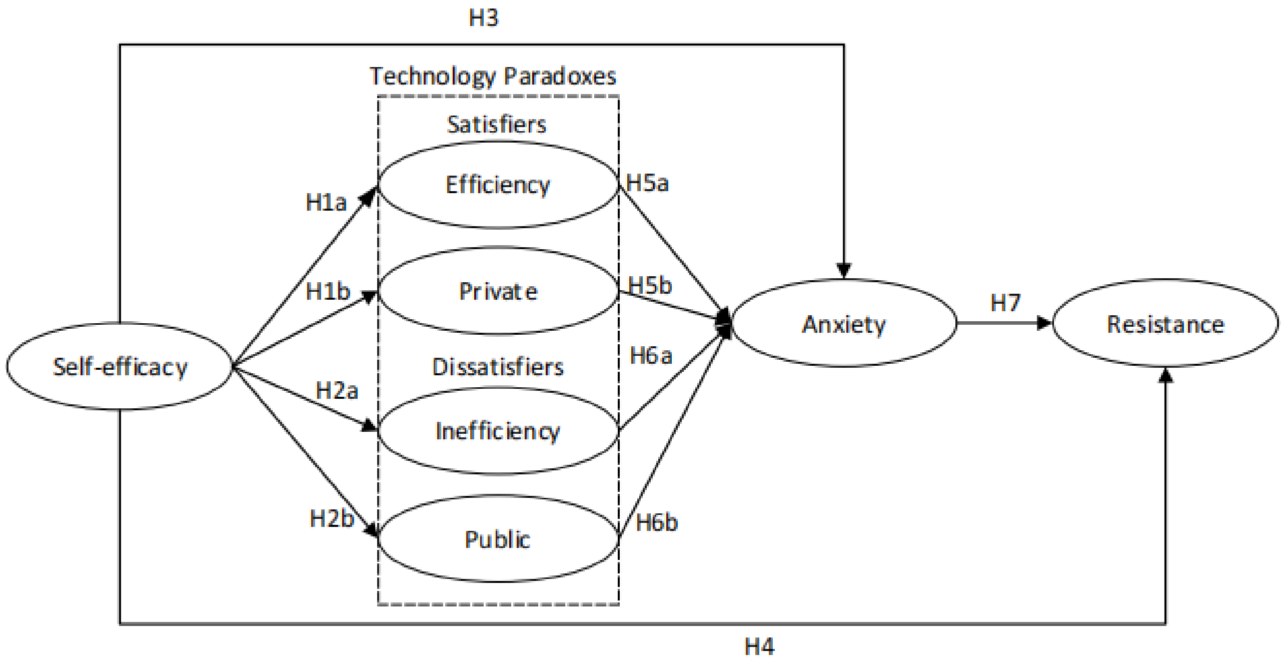

Figure 1 Research framework

According to self-efficacy theory, one's confidence in his/her capacity to use technology influenced by self-efficacy serves as the basis for judging the difficulty of using certain technologies (Bandura, 1977, 1982; Wood & Bandura, 1989). Self-efficacy has been shown to have positive impacts on perceived ease of use in previous studies. (Abdullah & Ward, 2016; Agudo-Peregrina et al., 2014; Chen et al., 2011; Hu et al., 2003; Zheng & Li, 2020). Individuals with high self-efficacy have more confidence in their skills to execute tasks quickly and efficiently than those with low self-efficacy. (Akhter, 2014). Furthermore, it has been discovered that self-efficacy lowers the privacy risk perceptions. (Chen & Chen, 2015; Dienlin & Metzger, 2016) and privacy concerns (Zhang et al., 2018b). Generally, individuals with high self-efficacy have the confidence to control their privacy and resolve issues as they use technologies. Therefore, high self-efficacy makes consumers less concerned about privacy and more willing to provide personal information to use a novel technology (Lee & Rha, 2016; Wasko & Faraj, 2005). Hence, the following hypotheses were proposed:

H1. Self-efficacy has positive associations with the satisfiers of technology paradoxes.

H1a. Self-efficacy has a positive association with efficiency.

H1b. Self-efficacy has a positive association with private.

H2. Self-efficacy has negative associations with the dissatisfiers of technology paradoxes.

H2a. Self-efficacy has a negative association with inefficiency.

H2b. Self-efficacy has a negative association with public.

Moreover, one's emotional reactions, such as anxiety and stress, are also associated with self-efficacy perceptions (Bandura, 1977; Hayashi et al., 2004; Moriuchi, 2021). Anxiety arises when people need to learn new technologies or applications. Having the competencies and confidence required to learn and use technology can reduce anxiety levels. According to Cazan et al. (2016) and Muris (2002), if an individual is confident in completing a task, he/she will have a positive mood. In contrast, individuals with low levels of self-efficacy often suffer from anxiety and panic due to the belief that they are incompetent. Previous studies have supported this negative relationship between self-efficacy and anxiety in terms of computer use (Durndella & Haagb, 2002; Ekizoglu & Ozcinar, 2010; Igbaria et al., 1995; Powell, 2013). Therefore, we proposed that:

H3. Self-efficacy has a negative association with anxiety.

Furthermore, early studies have found self-efficacy to influence one's attitude and usage intention toward technology (Celik & Yesilyurt, 2013; Gürcan, 2005; Jokisch et al., 2020; Lam & Lee, 2006; Mitzner et al., 2019). According to Ellen et al. (1991), regardless of whether the new technology is satisfactory, people with poor feelings of low self-efficacy are more likely to reject it in favor of alternatives they can manage and control. That is because feelings of low self-efficacy can cause anxiety and unease due to people's lack of confidence in their ability to manipulate new technologies. Therefore, when people do not have the confidence to be competent in learning and using new technologies, they tend to resist them. On the other hand, they may also choose to resist change to minimize anxiety and stress as a result of their lack of confidence (Tsai et al., 2020). That is, self-efficacy can not only affect resistance directly but also affect it through anxiety. Thus, we provided the following hypotheses:

H4. Self-efficacy has a negative association with resistance.

Technological products not only facilitate less effort or time but also lead to more effort or time (Mick & Fournier, 1998). Since no contact or physical interaction is required, using FRT can be very convenient and efficient for the end-users (Elloumi et al., 2021). It allows users to complete payments within a few seconds and dramatically improves efficiency (Zhong et al., 2021). However, users can also perceive inefficiency in poor conditions (e.g., angle, lighting, and distance of the subject to the camera) (Davis, 2014). Besides, despite the protection of some laws and policies, privacy issues arising from the use of FRT are still a major concern (Bowyer, 2004; Naker & Greenbaum, 2017; Raji et al., 2020). Thus, consumers can perceive the benefits (efficiency and private) of FRT and its potential adverse impacts (inefficiency and public) simultaneously (Introna & Nissenbaum, 2010).

Paradoxical situations encountered by technology users can provoke negative feelings, including anxiety and stress (Lee & Rha, 2016). According to Mick and Fournier (1998), anxiety and stress are likely to be stimulated by the conflict and ambivalence resulting from technology paradoxes. Specifically, the significant relationship between efficiency/inefficiency and anxiety/stress about mobile technology was confirmed quantitatively by Chae and Yeum (2010). In addition, the results of an interview undertaken by Bulmer et al. (2018) also revealed that the negative dimensions of technology paradoxes can evoke anxiety and stress to some extent. Similarly, with a qualitative approach, Wilson-Nash and Tinson (2021) found the effect of technology paradoxes on the elderly's emotions of conflict and anxiety in the use of digital technology. Drawing on this theoretical mechanism, we proposed that:

H5. The satisfiers of technology paradoxes have negative associations with on anxiety.

H5a. Efficiency has a negative association with anxiety.

H5b. Private has a negative association with anxiety.

H6. The dissatisfiers of technology paradoxes have positive associations with anxiety.

H6a. Inefficiency has a positive association with anxiety.

H6b. Public has a positive association with anxiety.

Anxiety is fear, sadness, tension, and other negative emotions or feelings caused by some stressful situations (Spielberger, 1983). Computer anxiety corresponding to computer use refers to various negative emotions or feelings (e.g., fear, sadness, and tension) experienced when an individual is considering using or really applying computer technology (Maurer, 1994; Scott

& Rockwell, 1997; Simonson et al., 1987). As mentioned above, it may result from a lack of confidence or experience in effectively operating a computer (Oyedele & Simpson, 2007). Another broader concept stemming from computer anxiety is technology anxiety. This anxiety focuses on the negative thoughts or feelings related to all general technological tools (Abdullah & Ward, 2016; Meuter et al., 2003). Therefore, in this study, the concept "anxiety" refers to "technology anxiety," which is the negative emotions or feelings that people have when they are thinking about or actually using FRT.

According to Compeau and Higgins (1995), users tend to avoid behaviors that cause anxiety. A voluminous body of research has empirically revealed that anxiety negatively influences usage intention (Cazan et al., 2016; Ekizoglu & Ozcinar, 2010; Lu & Su, 2009; McFarland & Hamilton, 2006; Meuter et al., 2003). For example, based on TAM, McFarland and Hamilton (2006) found that computer usage intention is significantly affected by computer anxiety. Similarly, Lu and Su (2009) argued that anxiety is an obstacle to using innovative systems, and they found that it is negatively related to a customer's intention to adopt mobile phones. Other scholars, such as Celik and Yesilyurt (2013) and Patil et al. (2020), indicated that anxiety negatively predicts users' attitudes toward technology. Despite extensive research on the relationship between anxiety and usage intention, few studies have explored this relationship in FRT usage settings. Furthermore, the current study adopted another construct—resistance instead of usage intention. Hence, we proposed the hypothesis as follows:

H7. Anxiety has a positive association with resistance.

4. Research methods

4.1 Sample

An online survey was conducted to explore the antecedents influencing the resistance of FRT, and the target participants were those who had experience of using the microfinance platforms in China. Besides, the survey added a series of questions for screening to ensure participants' experience with microfinance platforms. After filtering, 418 of the 542 questionnaires that were distributed were found to be valid.

Table 3 shows the respondents' demographic characteristics. Out of the 418 respondents, 186 (44.5%) were males, and 232 (55.5%) were females. According to the table, the 21–30 age group, which is 53.6%, has the most participants; the 31–40 age group is next with 37.3%, while participants over 40 and under 21 are 6.7% and 2.4%, respectively. Besides, the majority of participants have a bachelor's degree (70.3%). The demographic profile showed that our sample is primarily made up of young and educated respondents with innovative mindsets. The gender, age, and education distribution levels are consistent with the distribution of general consumers of online microfinance platforms in China. Indeed, the consumers of online microfinance platforms in China are mainly young and educated people who are also intense users of mobile phones and mobile payments (Ma et al., 2018; Qiu et al., 2019; Zhang et al., 2018a). Moreover, according to statistics, there are slightly more females than males who use microfinance platforms like Alibaba in China (Zhang et al., 2018a). As for the usage frequency of the microfinance platforms, 34.4% of respondents used microfinance platforms 2–5 times per year, and 28.7% used them 6–10 times per year. Among the respondents, 27.3% had used the facial recognition function of microfinance platforms before, and 71.7% had heard about it, though they had never used it.

4.2 Measurement

The formal questionnaire is comprised of 21 questions corresponding to each construct (see Appendix A). All questions were assessed with a 7-point Likert scale, ranging from “1 = strongly disagree” to “7 = strongly agree”. We initially undertook a pre-test to ensure the quality of the questionnaire. Subsequently, the questionnaire was modified by adjusting the questions that were not easy to understand. As for these measurement items, we referenced prior research and adapted them to the context of FRT usage in microfinance platforms.

4.3 Data analysis

In this paper, the two-step procedure of structural equation modeling (SEM) analysis (Anderson & Gerbing, 1988) was performed using AMOS 24 and SPSS 23. First, we examined the measurement model based on confirmatory factor analysis (CFA), including model fit indices, reliability, convergent validity, and discriminant validity. Afterward, we evaluated the structural model by testing our hypotheses. In addition, the mediating effects of technology paradoxes and anxiety between self-efficacy and resistance were tested.

5. Results

5.1 Measurement model

To evaluate the model fit indices, we employed several common indicators, including the ratio of chi-square to degrees-of-freedom ($\chi 2$/d.f.), comparative fit index (CFI), goodness-of-fit index (GFI), Tucker–Lewis index (TLI), normed fit index (NFI), parsimony comparative fit index (PCFI), parsimony goodness-of-fit index (PGFI), and root mean square error of approximation (RMSEA). As observed, $\chi 2$/d.f. was within the acceptable limit of 3.0

(Kline, 2015; Tabachnick et al., 2007). Otherwise, CFI, GFI, TLI, and NFI all above the 0.9 criterion. (Bentler & Bonett, 1980; Hu & Bentler, 1999; Wang & Chiu, 2011). The respective values of PCFI and PGFI were above the recommended threshold of 0.5 (Mulaik, 2009). McDonald and Ho (2002) also suggested that RMSEA values below 0.05 indicate a "good" fit, while values below 0.08 indicate an "acceptable" fit. The RMSEA value in this research was 0.039. Overall, the model fit indexes shown in Table 4 indicated that the measurement model was fitted to our data well.

As for reliability, we calculated the value of Cronbach's α to ensure the internal consistency of each construct. Generally, its value varies from 0 to 1, and the greater it is, the better. According to Hair et al. (2010), values of 0.6 to 0.7 are acceptable, and values above 0.7 are considered to be excellent. The Cronbach's α values of efficiency, inefficiency, private, public, self-efficacy, anxiety, and resistance were 0.851, 0.864, 0.915, 0.937, 0.857, 0.897. and 0.905, respectively (see Table 5). It could be seen that all the values were above 0.8. This result, therefore, indicated the excellent reliability of the model.

To examine convergent validity, we followed three criteria recommended by Hair et al. (2010) and Fornell and Larcker (1981): a) factor loadings should be above 0.7; b) each construct's composite reliability (CR) should exceed 0.7; and c) each construct's average variance extracted (AVE) should be above 0.5. From Table 5, all CR and factor loadings values were above 0.7. The AVE values were all over 0.6. Accordingly, the level of convergent validity was also satisfactory.

The Fornell-Lacker criterion (Fornell & Larcker, 1981), one of the most commonly used criteria, was used to assess discriminant validity. This criterion suggests that the square root of AVE should be above the correlation coefficient of the constructs. Table 6 showed that this requirement was met, indicating favorable discriminant validity of the measurement model.

5.2 Structural model

We used the same fit criteria to evaluate the structural model. As shown in Table 4, the values of $\chi2$/d.f., CFI, GFI, TLI, NFI, PCFI, PGFI, RMSEA were 2.279, 0.970, 0.918, 0.964, 0.948, 0.822, 0.707, 0.055, respectively. It showed that all these fit indexes met the recommended criteria.

Our research model and the results of hypothesis testing are exhibited in Figure 2 and Table 7. It turned out that all the hypotheses were strongly supported (significant at *p*-value < 0.01), except for H5 (H5a and H5b). As expected, self-efficacy was shown to be positively associated with efficiency ($\beta = 0.796$, $p < 0.001$) and private ($\beta = 0.844$, $p < 0.001$) and a negative association with inefficiency ($\beta = -0.731$, $p < 0.001$), public ($\beta = -0.707$, $p < 0.001$), anxiety ($\beta = -0.626$, $p < 0.001$), and resistance ($\beta = -0.666$, $p < 0.001$). Hence, the hypotheses H1, H2, H3, and H4 were accepted. Besides, the positive associations of inefficiency ($\beta = 0.159$, $p < 0.01$) and public ($\beta = 0.493$, $p < 0.001$) with anxiety were supported, whereas efficiency ($\beta = 0.22$, $p < 0.01$) and private ($\beta = 0.134$, $p > 0.05$) did not share the hypothesized association with anxiety. In contrast, anxiety was found to be positively influenced by efficiency and to have no relationship with private. Therefore, H5 was rejected and H6 was accepted. Finally, the hypothesized positive association of anxiety with resistance ($\beta = 0.317$, $p < 0.001$) was confirmed. H7 was also accepted.

The percentage variance of resistance was 88%, indicating the strong predictive power of the proposed model. Besides, the percentage variances of efficiency, private, inefficiency, and public explained by self-efficacy were 63%, 71%, 53%, and 50%, respectively. ogether, self-efficacy, efficiency, private efficiency, inefficiency, and public efficiency explained 80% of the variance in anxiety.

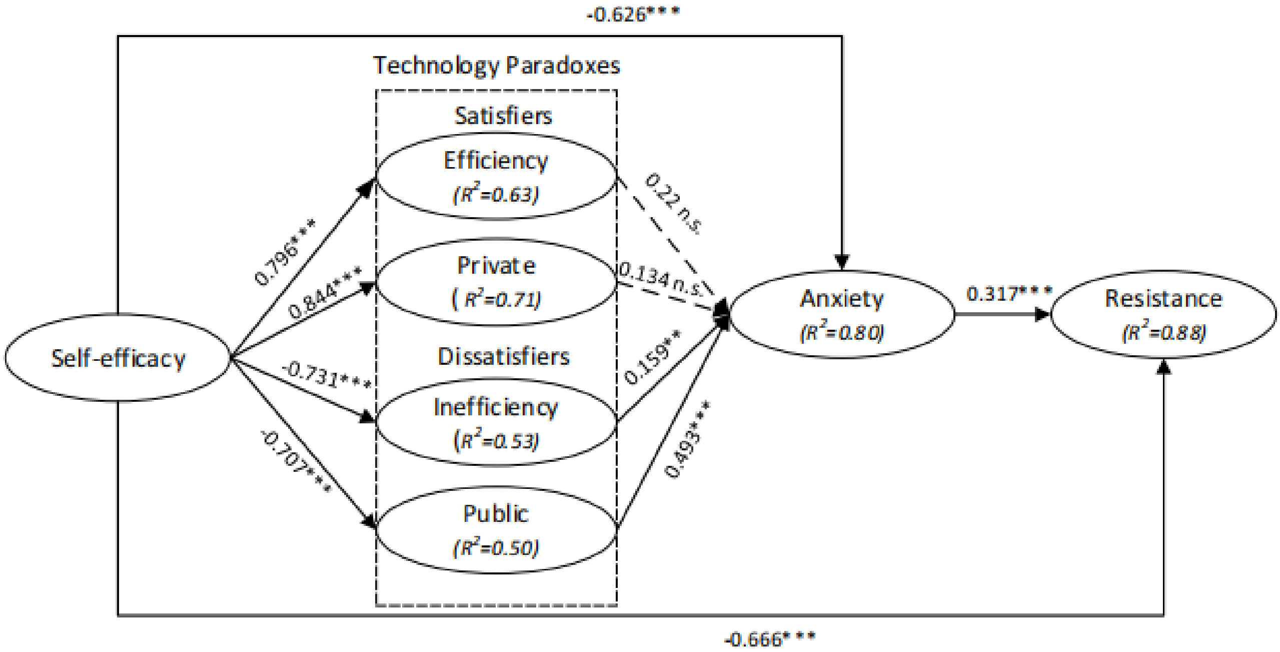

Figure 2 Results of hypothesis testing. Notes: ***p < 0.001; **p < 0.01; *p < 0.05.

5.3 Testing of mediating effects

Based on the bootstrapping technique, this research further verified the effects of mediators. The parameters set are as follows: a) 5000 bootstrap samples; b) 95% bias-corrected confidence interval (CI); and c) 95% percentile confidence interval (CI). The significant mediating effects could be confirmed if the 95% confidence interval does not involve zero (Chen & Xu, 2019). With reference to this requirement, three sets of mediators could be found (see Table 8). At first, self-efficacy had a positive effect on resistance via an indirect path from efficiency to anxiety (β = 0.087, Bias-corrected 95% CI = 0.027 to 0.182, Percentile

95% CI = 0.017 to 0.165). Second, self-efficacy has a negative effect on resistance via an indirect path from public to anxiety (β = -0.174, Bias-corrected 95% CI = -0.295 to -0.092, Percentile 95% CI = -0.288 to -0.089), or via anxiety (β = -0.312, Bias-corrected 95% CI = -0.527 to -0.169, Percentile 95% CI = -0.511 to -0.162).

5.4 Model stability

To assess the stability of the model, we still utilized the bootstrap technique by recreating 500 samples from the original sample set through the AMOS software. This technique provides us with an effective way to ensure the stability of the path coefficients and correlations (Nedra et al., 2019). This study followed the two steps that Ievers-Landis et al. (2011) proposed to conduct the stability test. First, there should not be much difference (bias) between the mean bootstrap estimates and the original estimates. Second, the mean bootstrap samples' standard error (SE) should be above the SE-bias between the bootstrap samples and the original model. Table 9 showed that the bias was small since the mean bootstrap estimates were very close to the initial sample estimates; SE-bias for each path was less than SE. Thus, the study concluded that the estimated model was stable and unbiased.

6. Discussion

The present study is a pioneer to evaluate the role of FRT in the microfinance context, especially microfinance customers' resistance toward FRT. It adds to the body of knowledge by creating a theoretical model that integrates the technology paradox framework (Jarvenpaa & Lang, 2005; Mick & Fournier, 1998) and self-efficacy theory (Compeau & Higgins, 1995). Besides, it turned out that this model had a good fit and strong predictive power. Our findings revealed that the antecedents—self-efficacy, technology paradoxes, and anxiety—were all related to usage intention toward FRT. In particular, we demonstrated two primary technology paradoxes related to FRT usage—efficiency/inefficiency and private/public.

First, the results of hypothesis testing showed that self-efficacy significantly influences technology paradoxes, anxiety, as well as resistance. These findings supported the social cognitive theory (Compeau & Higgins, 1995), which was consistent with previous research on how self-efficacy affects users' anxiety (Cazan et al., 2016) and usage intention for FRT (Li et al., 2020; Moriuchi, 2021). Although existing literature has shown the positive impact of self-efficacy on perceived benefits (Horacek et al., 2002) and perceived ease of use (Abdullah & Ward, 2016; Zheng & Li, 2020), this study specifically revealed that self-efficacy could positively influence users' perception of efficiency and private (satisfiers of technology paradoxes). In contrast, the perception of inefficiency and public (dissatisfiers of technology paradoxes) could be negatively influenced by self-efficacy. These results mean that, in the case of FRT usage in microfinance platforms, customers with low self-efficacy tend to make negative judgments and be anxious. Also, they are reluctant to use the facial recognition of microfinance platforms.

More importantly, the results of the mediating effects test showed that self-efficacy also indirectly influenced resistance via efficiency, public, and anxiety. While prior studies have indicated self-efficacy significantly influences anxiety (Durndella & Haagb, 2002; Ekizoglu & Ozcinar, 2010; Powell, 2013), usage intention (Celik & Yesilyurt, 2013; Jokisch et al., 2020; Mitzner et al., 2019), few of them have discussed the role of anxiety in mediating the relationship between self-efficacy and resistance. This study also found the mediating role of technology paradoxes between self-efficacy and resistance for the first time. This finding implies that the effect of microfinance platform users' self-efficacy on resistance toward FRT can be mediated by their perception of efficiency, privacy issues, and anxiety.

Moreover, the current study suggested that the relationship between technology paradoxes (including efficiency, inefficiency, private and public) and anxiety varies. First, surprisingly, efficiency is positively related to anxiety. This result could imply that customers regard efficiency as a conflict rather than a benefit. Generally, the high efficiency of FRT could reflect technological progress that could generate anxiety (Mokyr et al., 2015). This is because the advancement of certain technologies often means that they will be more widely used. However, considering privacy and security issues are still unresolved, the wide application of FRT will increase users' anxiety. Second, it turned out that private cannot directly influence anxiety, which contradicted past research (Chae & Yeum, 2010). One possible reason for the insignificant relationship between private and anxiety is that although the privacy policies of microfinance platforms try to protect users' personal information, users are also concerned about the effectiveness and transparency of these policies (Gong et al., 2019). Therefore, even if users are aware of the privacy protection offered by the platforms, their anxiety can not be reduced. Finally, consistent with existing studies (Bulmer et al., 2018; Wilson-Nash & Tinson, 2021), the dissatisfiers of technology paradoxes (both inefficiency and public) positively correlate with anxiety. It shows that customers of the microfinance platforms are more concerned about the inefficiency of FRT usage and the leakage personal information, which can invoke their negative feelings.

Finally, a positive correlation was found between anxiety and resistance, consistent with prior theories and research (Ekizoglu & Ozcinar, 2010; Lu & Su, 2009; McFarland & Hamilton, 2006; Meuter et al., 2003). However, in terms of FRT application, research taking anxiety into consideration is scarce. Although Rasiah and Yen (2020) assumed anxiety was a crucial determinant affecting usage intention for biometric authentication, this hypothesis was not confirmed. Similarly, while Gao et al. (2021) pointed out that anxiety played a crucial role in using FRT, they did not directly estimate its effect. This study addressed this gap by empirically demonstrating the positive relationship between anxiety and resistance to FRT in microfinance settings. In other words, for customers of the microfinance platforms, a high level of anxiety due to technology paradoxes (inefficiency and public) restrains them from using FRT.

7. Conclusions

7.1 Theoretical implications

Recently, FRT has been extensively applied in various areas, including online microfinance platforms. Despite an increasing volume of studies on the usage intention of FRT, literature focusing on users' acceptance or resistance to using FRT in the microfinance field is scarce. This research sets out to fill this gap by empirically exploring the antecedents of resistance behavior. Based on prior theories and studies, our research model that combines the technology paradox framework and self-efficacy theory was proposed. Besides, an online survey was conducted, and 418 valid questionnaires were received. Finally, based on the SEM analysis, we tested the measurement and structural models by using AMOS 24 and SPSS 23. To the best of the authors' knowledge, this is the first study analyzing behaviorial intentions to FRT on the basis of technology paradoxes. This research has profound theoretical implications.

First, based on the technology paradox framework, this paper recognized two primary paradoxes (efficiency/inefficiency and private/public) and anxiety as the antecedents of resistance to FRT usage. Compared with existing studies (Ciftci et al., 2021; Liu et al., 2021), this study examined not only privacy-related factors but also functional factors (e.g., efficiency) and psychological factors (e.g., self-efficacy). The results also proved the existence of technology paradoxes experienced by microfinance customers when using FRT. In addition, this study verified the crucial role of anxiety in affecting FRT adoption by empirically demonstrating the positive relationship between anxiety and resistance to FRT. More importantly, it demonstrated the mediating role of technology paradoxes (efficiency and public) and anxiety between self-efficacy and resistance.

Second, the present study expanded the technology paradox framework by introducing the self-efficacy theory. As expected, resistance was influenced both directly and indirectly by self-efficacy. It highlighted the significance of psychological factors (e.g., self-efficacy, anxiety) in affecting users' adoption decisions. This research advances the literature on both microfinance and FRT applications by providing a quantitative understanding of how self-efficacy and technology paradoxes affect resistance. Additionally, considering the rationality and explanatory power of the research model, it can also serve as the baseline for exploring usage intention toward other emerging technologies.

7.2 Practical implications

Microfinance plays a key role in fighting against financial exclusion and promoting entrepreneurship in developing countries (Annim, 2012; Bassem, 2008). During the last decade, microfinance providers also greatly benefited from the advent of ICT applications, especially AI technologies focused on in this paper. These ICT tools can help microfinance providers improve efficiency, reduce costs, and alter the way individuals access financial services (Moro-Visconti, 2021). Considering the substantial contribution of ICT in the fight against COVID-19, there is an urgent need to examine the role of ICT in society and achieve its tremendous potential. The emerging microfinance platforms based on ICT have been updating their functions and services, including introducing FRT. However, they must take customers' needs into consideration to provide efficient and effective financial services. It is necessary to analyze whether and how FRT can be promoted from the customer's perspective. This study has significant practical implications and sheds new light on the issues regarding Chinese users' resistance toward FRT. It also provides guidelines for microfinance providers, government agencies, and technology designers.

First, this study helps microfinance providers to understand the paradoxes experienced by FRT users and take corresponding measures. On the one hand, efficiency and profitability have become central issues for microfinance in the increasingly competitive environment (Kauffman & Riggins, 2012). However, microfinance providers should not only improve their own efficiency but also consider their customers' perceptions of efficiency. In addition, while a range of privacy regulations and practices related to privacy have been launched to protect personal information, microfinance customers are still worried about privacy leakage and are reluctant to use FRT. As a result, microfinance platforms and the government should not only advance relevant laws and policies but also give customers control over their personal information. For example, microfinance platforms could inform users of what and how personal information will be used in detail to ensure the effectiveness and transparency of privacy policies. Besides, policymakers need to modify long and complicated clauses to make them easier for ordinary people to understand (Zheng, 2021).

Moreover, it raises awareness of the importance of users' confidence or self-efficacy in using FRT. To build customers' confidence and ease their anxiety, microfinance providers need to increase the frequency of FRT use through rewards and other ways and provide users with the necessary education and training to encourage them to use FRT (Salanova et al., 2000). For example, the platforms could provide a guide to FRT usage (including solutions when problems arise) and direct customers to search for and read it. In addition, a good customer experience can also enhance users' confidence to continue using. Therefore, microfinance providers should turn their attention to the users' experience mentioned above. In summary, all these measures will effectively mitigate users' anxiety, which in turn influences customers' behavioral intentions toward the facial recognition function of microfinance platforms.

Technology designers can benefit from this research by getting a better understanding of users' needs, thereby improving FRT performance and promoting its usage. To enhance the effectiveness of FRT systems, on the one hand, they should refine existing datasets and continuously test the system to recognize faces of different genders and skin tones (Garvie & Frankle, 2016). On the other hand, technology designers should continue to update the FRT system to adapt to a range of constraint factors, such as angle, lighting, facial expression, and make-up (Davis, 2014). In addition, this study suggests that technology designers should make a trade-off between efficiency and privacy. It encourages designers to take both system functionality and its impacts on users' privacy into consideration (Lahlou et al., 2005).

7.3 Limitations and further research

There are a few limitations deserving further research: First, the generalisability of these findings is limited as this study focuses on FRT users of the online microfinance platforms in China. Future work across different countries and sectors is needed to validate these research findings. Second, the majority of our sample is composed of young and highly educated people, who may be more receptive to FRT due to their familiarity with the internet and mobile technologies. This makes this study less generalizable to the usage intentions of the average FRT users. Accordingly, the usage intentions of the elderly, less educated, and other potential users should be further discussed. Third, while many factors affect the usage intention toward FRT, this study merely examined the framework integrating technology paradoxes and self-efficacy. Based on the technology paradox framework, only "anxiety", a negative factor, was included in our research model. Hence, future research could take some positive factors (e.g., "liking", "satisfaction", and "trust") into consideration beyond this framework. Fourth, given that this study only assumed that technology paradoxes affect resistance through anxiety aligned with the technology paradox framework, future studies could further examine the direct relationships between them. Finally, our research results may be influenced potentially by some demographic variables such as respondents' gender, age, education, and income. Compared with traditional banking users, microfinance users will also have differences in individual wealth. Future research should incorporate these variables as moderators to determine differences in consumer samples.

Table 1 Existing literature on exploring the acceptance of FRP

Article	Country	Theoretical Basis	Findings of the study
Dong and Hai (2019)	China	UTAUT and TAM	First, perceived ease of use, perceived risk, perceived usefulness are major drivers of usage intention. Second, subject norm, system quality, and perceive enjoyment indirectly affect usage intention.
Zhang and Kang (2019)	China	_	First, security, social image, safety, expected effort, visibility influence usage intention. Second, perceived usefulness plays a mediating role. Third, openness characteristic moderates the effects of expected effort and security on usage intention.
Li et al. (2020)	China	Privacy calculus theory	First, threat appraisals and coping appraisals significantly influence usage intention. Second, the benefit-risk analysis shapes behaviorial intentions. Third, personal innovativeness is recognized as a moderator.
Zhong et al. (2021)	China	TAM	Factors such as perceived enjoyment, users' attitudes, personal innovativeness, and facilitating conditions are major determinants of usage intention.
Liu et al. (2021)	China	Innovation resistance theory, Privacy calculus theory	Perceived benefits, privacy concerns, perceived effectiveness of privacy, and perceived privacy risk influence users' resistance to FRP.
Hu et al. (2021)	China	_	First, perceived value, perceived value and trust significantly influence behavioral intentions toward FRP. Second, the correlation between usage intention and perceived value is moderated by information sensitivity.
Zhang et al. (2021)	China	_	First, the features of the FRP system, such as security, reliability convenience, and non-contact influence user innovation resistance. Second, user innovation resistance negatively affects usage intention.
Moriuchi (2021)	America	ToM and UTAUT	First, customers prefer to use FRP in stores than online. Second, trust and attitude have mediating effects on usage intention. Third, self-efficacy has moderating effects between performance expectation, perceived risk, and usage intention.

Notes: TAM - technology acceptance model; ToM - theory of mind; UTAUT - unified theory of acceptance and use of technology.

Table 2 Operational definition

Constructs	Definition	Source
Self-efficacy	Confidence in one's capability to undertake specific actions.	Compeau and Higgins (1995)
Efficiency	When using a technology, users can perceive they spend less effort or time on certain activities.	Mick and Fournier (1998)
Inefficiency	When using a technology, users can perceive they spend more effort or time on certain activities.	Mick and Fournier (1998)
Private	When using a technology, users can perceive control over the disclosure and subsequent use of personal information.	Xu et al. (2008)

Constructs	Definition	Source
Public	When using a technology, users can perceive privacy risks or losses resulting from the internet disclosure of personal information.	Xu et al. (2008)
Anxiety	Fear, sadness, tension, and other negative emotions or feelings caused by some stressful situations.	Spielberger (1983)
Resistance	A natural psychological state in which the perceived consequences (e.g., loss of power) are unfavorable.	Ang and Pavri (1994); Kang and Kim (2009)

Table 3 Sample characteristics

Characteristics	Frequency	Percentage (%)
Gender		
Female	232	55.5
Male	186	44.5
Age		
20 years or less	10	2.4
21-30 years	224	53.6
31-40 years	156	37.3
41 years or above	28	6.7
Education		
High school or below	25	6.0
College degree	60	14.4
Bachelor degree	294	70.3
Graduate degree	39	9.3
Microfinance platforms usage per year		
1 time	64	15.3
2-5 times	144	34.4
6-10 times	120	28.7
10 times or above	90	21.5
Have you heard of or used FRT?		
Never heard of	4	1.0
Heard of it but never used it	300	71.7
Have used it before	114	27.3

Table 4 Fit indices for measurement and structural models

Fit index	Recommended level	Measurement model	Structural model
$\chi 2$/d.f.	< 3.0	1.639	2.279
CFI	> 0.9	0.986	0.970
GFI	> 0.9	0.942	0.918
TLI	> 0.9	0.982	0.964
NFI	> 0.9	0.965	0.948
PCFI	> 0.5	0.789	0.822
PGFI	> 0.5	0.685	0.707
RMSEA	<0.05 (good fit) < 0.08 (acceptable fit)	0.039	0.055

Notes: χ2/d.f. - chi-squared to degrees of freedom; CFI - comparative fit index; GFI - goodness-of-fit index; TLI- Tucker–Lewis index; NFI - normed fit index; PCFI - parsimony comparative fit index; PGFI - parsimony goodness-of-fit index; RMSEA - root mean square error of approximation.

Table 5 Reliability and convergent validity

Construct	Item	Factor Loading	SMC	Cronbach's Alpha	CR	AVE
	EF1	0.862	0.743			
Efficiency	EF2	0.747	0.558	0.851	0.852	0.659
	EF3	0.822	0.676			
	IE1	0.828	0.686			
Inefficiency	IE2	0.829	0.687	0.864	0.864	0.68
	IE3	0.817	0.667			
	PR1	0.904	0.817			
Private	PR2	0.88	0.774	0.915	0.915	0.782
	PR3	0.869	0.755			
	PU1	0.914	0.835			
Public	PU2	0.914	0.835	0.937	0.939	0.836
	PU3	0.915	0.837			
	SE1	0.872	0.76			
Self-efficacy	SE2	0.791	0.626	0.857	0.858	0.669
	SE3	0.788	0.621			
	A1	0.897	0.805			
Anxiety	A2	0.922	0.85	0.897	0.901	0.754
	A3	0.779	0.607			
	R1	0.857	0.734			
Resistance	R2	0.904	0.817	0.905	0.905	0.761
	R3	0.856	0.733			

Notes: AVE - Average variance extracted; SMC - Squared multiple correlations.

Table 6 Discriminant validity of the construct

Construct	Efficiency	Inefficiency	Private	Public	Self-efficacy	Anxiety	Resistance
Efficiency	0.812						
Inefficiency	-0.719	0.825					
Private	0.655	-0.601	0.884				
Public	-0.446	0.643	-0.698	0.914			
Self-efficacy	0.766	-0.658	0.801	-0.654	0.818		
Anxiety	-0.518	0.692	-0.678	0.832	-0.754	0.868	
Resistance	-0.716	0.694	-0.787	0.734	-0.879	0.852	0.872

Notes: Diagonal values are the square root of average variance extracted （AVE）. Off-diagonal values are the correlation estimates.

Table 7 Results of hypothesis testing

Hypothesis	Path	Estimate	S.E.	t-value	p-value	Conclusion
H1a	Self-efficacy → Efficiency	0.796***	0.06	13.973	0.000	Supported
H1b	Self-efficacy → Private	0.844***	0.079	15.595	0.000	Supported

Hypothesis	Path	Estimate	S.E.	t-value	p-value	Conclusion
H2a	Self-efficacy → Inefficiency	-0.731***	0.074	-12.647	0.000	Supported
H2b	Self-efficacy → Public	-0.707***	0.09	-13.529	0.000	Supported
H3	Self-efficacy → Anxiety	-0.626***	0.21	-4.955	0.000	Supported
H4	Self-efficacy → Resistance	-0.666***	0.1	-10.487	0.000	Supported
H5a	Efficiency → Anxiety	0.22**	0.113	3.101	0.002	No supported
H5b	Private → Anxiety	0.134	0.085	1.787	0.074	No supported
H6a	Inefficiency → Anxiety	0.159**	0.071	2.899	0.004	Supported
H6b	Public → Anxiety	0.493***	0.054	8.867	0.000	Supported
H7	Anxiety → Resistance	0.317***	0.052	5.812	0.000	Supported

Notes: ***p < 0.001; **p < 0.01; *p < 0.05.

Table 8 Results of mediating effects

Path	Indirect Effect	SE	Bias-corrected 95%CI			Percentile 95%CI		
			Lower	Upper	P	Lower	Upper	P
indS1	0.087	0.038	0.027	0.182	0.006	0.017	0.165	0.014
indS2	-0.058	0.041	-0.15	0.017	0.114	-0.132	0.029	0.205
indS3	0.056	0.042	-0.027	0.14	0.151	-0.033	0.136	0.181
indS4	-0.174	0.05	-0.295	-0.092	0.000	-0.288	-0.089	0.000
indS5	-0.312	0.091	-0.527	-0.169	0.000	-0.511	-0.162	0.000

Notes: indS1: Self-efficacy → Efficiency → Anxiety → Resistance; indS2: Self-efficacy → Inefficiency → Anxiety → Resistance; indS3: Self-efficacy → Private → Anxiety → Resistance; indS4: Self-efficacy → Public → Anxiety → Resistance; indS5: Self-efficacy → Anxiety → Resistance.

Table 9 Bootstrapped standardized regression weights

Correlations	Original estimate	Mean bootstrap estimate	Difference (Bias)	SE	SE-bias
Self-efficacy → Efficiency	0.796	0.794	0.002	0.031	0.001
Self-efficacy → Private	0.844	0.843	0.001	0.023	0.001
Self-efficacy → Inefficiency	-0.731	-0.730	-0.001	0.051	0.002
Self-efficacy → Public	-0.707	-0.706	-0.001	0.032	0.001
Self-efficacy → Anxiety	-0.626	-0.630	0.004	0.144	0.006
Self-efficacy → Resistance	-0.666	-0.663	-0.003	0.068	0.003
Efficiency → Anxiety	0.220	0.214	0.006	0.091	0.004
Private → Anxiety	0.134	0.133	0.001	0.096	0.004
Inefficiency → Anxiety	0.159	0.148	0.011	0.108	0.005
Public → Anxiety	0.493	0.495	-0.002	0.073	0.003
Anxiety → Resistance	0.317	0.319	-0.002	0.069	0.003

Notes: SE: standard error

Appendix A Measurement items

Construct	Questionnaire Items	Adapted from
Efficiency	EF1. Using the facial recognition function of microfinance platforms improves my efficiency.	Garrity (2012); Park and Zhang

Construct	Questionnaire Items	Adapted from
	EF2. Using the facial recognition function of microfinance platforms enables me to access the microfinance platforms faster. EF3. Most of the time, using the facial recognition function of microfinance platforms is convenient to use.	(2021)
Inefficiency	IE1. Figuring out how to use the facial recognition function of microfinance platforms is usually too time-consuming. IE2. Using the facial recognition function of microfinance platforms always seems to take longer than I expected. IE3. Using the facial recognition function of microfinance platforms is often more complicated than needs to be.	Garrity (2012); Park and Zhang (2021)
Private	PR1. If I use the facial recognition function of microfinance platforms, I believe that how these platforms use my personal information is in my control. PR2. If I use the facial recognition function of microfinance platforms, I believe that what personal information is released by microfinance platforms is in my control. PR3. If I use the facial recognition function of microfinance platforms, I believe that I can control my personal information provided to the microfinance platforms.	Liu et al. (2021); Xu et al. (2008)
Public	PU1. Using the facial recognition function of microfinance platforms makes me worried about the amount of personal information acquired by microfinance platforms. PU2. Using the facial recognition function of microfinance platforms makes me worried that my personal data might be accessed by unauthorized persons. PU3. Using the facial recognition function of microfinance platforms makes me worried that my personal data might be misused by microfinance platforms.	Liu et al. (2021); Xu et al. (2008)
Resistance	R1. I am reluctant to utilize the facial recognition function of microfinance platforms. R2. I insist on using passwords rather than the facial recognition function of microfinance platforms. R3. I would not recommend the facial recognition function of microfinance platforms to others.	Liu et al. (2021); Kang and Kim (2009); Lee (2020);
Self-efficacy	SE1. I am sure that I have the ability to overcome difficulties brought by the facial recognition function of microfinance platforms. SE2. Compared with others, I have the confidence to conduct any type of transaction through face recognition and any other authorization method. SE3. I have the confidence to overcome certain difficult financial transactions due to the use of the facial recognition function of microfinance platforms.	Moriuchi (2021)
Anxiety	A1. It makes me nervous to think about losing personal information due to incorrect use of the facial recognition function of microfinance platforms. A2. I am hesitant to use the facial recognition function of microfinance platforms because I'm afraid of making mistakes that I can't correct. A3. I fear that mistakes brought by the facial recognition function of microfinance platforms are potentially devastating.	Patil et al. (2020) Rana et al. (2017); Lu and Su (2009); Johnson et al. (2008)

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